INNOVATION PERCEPTION OF KNOWLEDGE-INTENSIVE BUSINESS SERVICES IN THE TWITTERSPHERE

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ABSTRACT

The rapid diffusion of Twitter as a social media tool has made it suitable to be used for big data quantitative research. KIBS and their clients use this platform to share, engage and get information fostering their innovation processes. Using a mix of quantitative and qualitative methods, we have contrasted interviews from nine KIBS with 16702 tweets mentioning the name of these firms. We have focused on understanding the perception and focus of the innovation management strategy in this sector. The digital transformation was found to be the main driver of KIBS innovative activities. We discuss why the importance of digitalization and the way in which large KIBS achieve their innovation objectives, which differs from the practices done by SME. Finally, an agenda for further research is proposed as well.

Keywords*: Innovation Management; Twitter; Natural Language Processing; KIBS; Consulting Firms*

1. INTRODUCTION

Consulting firms are usually considered to be part of Knowledge-Intensive Business Services (KIBS). KIBS are such organizations that primarily add value through the accumulation, creation or dissemination of knowledge for the purposes of the customer and which have other businesses as their main clients (Miles, 2005)

Private companies or organizations; relying heavily on KIBS to co-produce innovations (Aarikka-Stenroos & Jaakkola, 2012; den Hertog, 2000; Santos-Vijande et al., 2013). Consulting firms are a major source of knowledge-based innovation because of their expertise, structure, diversification and continuous creation/recombination of knowledge (Anand et al., 2007; Miles, 2005; Wright et al., 2012).

Twitter Social Network is a prime platform for developing a framework that allows for information retrieval to support analysis and management of Big Data on social media (García-Crespo et al., 2017)

Twitter could be considered part of the continuous innovation ecosystem of KIBS, in other words, it is part of the community of actors interacting with a unique system to produce inter-organizational streams of continuous innovation (Gastaldi et al., 2015)

To our best knowledge, only a few works address the topic of innovation in the Twittersphere (García-Crespo et al., 2017), but none of them focus on KIBS nor the interlink between the firm's innovation management, the image created by the firm via social media such as Twitter and the perception about the firm's innovation by the audience in the Twittersphere. The aim of this study is to contribute to fill this research gap.

This article was organized as follows: literature review has been detailed in the next section. The methods section detailed our data collection of tweets and interviews to describe the text mining techniques on social networks and our analytical output. Then, the results of the statistical analysis performed on qualitative data from the interviews and the quantitative data analyzed through machine learning techniques. A discussion regarding the results and the conclusion is presented in the last section.

2. LITERATURE REVIEW

A brief survey of previous works in the area.

2.1 KNOWLEDGE-INTENSIVE BUSINESS SERVICES

Knowledge-intensive business services (KIBS) provide services based on professional knowledge. In that industry, transactions consist of knowledge and outputs are often intangible (Leiponen, 2006). Different authors have studied the definition and role of KIBS, some views are summarized in Table 1.

Authors	Main Contribution
(Muller & Doloreux, 2009)	Characteristics and the role of KIBS
(Amara, Landry, & Traoré, 2008)	Features and measurements for innovation of KIBS
(Smedlund, 2008)	The role of KIB for intellectual development
(Muller & Zenker, 2001)	KIBS as activities for knowledge production
(Miles, 2005)	KIBS and the European Economy
(Corrocher, Cusmano, & Morrison, 2011)	KIBS Typology
(Consoli & Elche-Hortelano, 2010)	KIBS as input and output for innovation

Table 1. List of studies about KIBS and innovation management

Derived from this literature review, it can be inferred that there are three main perspectives about what KIBS are:
i) innovative organizations, being innovative agents within the system.
ii) sources of external information among other sources.
iii) knowledge facilitators supporting their users' innovation processes and the knowledge transfers between organizations, industries, networks, and innovation systems and their clusters.
Innovation management in the context of consulting firms is a has been underexplored but set a perfect environment to understand for about innovation in services due to the firm's' innovation capacity that depends on its sources of internal information (R&D capacity, use of advanced technologies, use of high value-added manufacturing practices) and its sources of external information (Amara et al., 2008)
Consulting firms are considered as sources of external information, as KIBS they are facilitators of activities having knowledge as their main input and output (Desmarchelier et al., 2013; Toivonen et al., 2008).

2.2 USE OF TWITTER IN SOCIAL SCIENCES

The Twitter environment and the influence of several entities such as organizations, political parties, candidates, products, among others, have been increased since the irruption of web 2.0. Public information in Twitter as a data source for opinion mining (Pak & Paroubek, 2010), due to the volume of information makes it an attractive research field, getting interesting business-oriented insights, recommendations, and analytical output, for consultancy firms and innovation knowledge.

There is a restrictive factor that has limited to maximum 140 characters, which forces the conciseness and entails an expansive factor that allows tweets to reach far (Congosto et al., 2011). Likewise, Twitter users´ have propagation capacity proportional to their number of followers, but the message can be retransmitted by the followers of the followers without any limitation, additionally is possible to mention other users or classify messages by hashtags.

Focusing our research on Twittersphere and organizations, there are previous works that have addressed the importance of this social network (Cody et al., 2015; Martinez-Camara et al., 2012) in areas such as business intelligence, recommender systems, graphical interfaces and visual assistance, and even social issues as a climate change, where the information source and discussion is becoming a commonplace.

2.3 Machine Learning Techniques in Spanish Corpus

Machine learning, defined as a combination of several disciplines such as statistics, information theory, algorithms, probability and functional analysis (Munoz, 2014) and it explores the construction of algorithms for predictions, classification, through building models from sample inputs.

Previous works have addressed the use of machine learning techniques in Spanish language corpora (Dubiau & Ale, 2013) classifying text under supervised and unsupervised learning methods, founded that pre-processing stage is crucial for the results. In other cases, it was performed an automatic sentiment analysis (Cesteros et al., 2015; Molina-Gonzalez et al., 2014; Pla & Hurtado, 2014) in order to get the polarity of a defined Spanish corpus.

The use of posts in social networks, has useful applications in social sciences, providing large possibilities analyzing trends, evaluation of public opinions where researchers pursue the significance in such procedures with the aid of Natural Language Processing (henceforward NLP), defined as a computational treatment of opinion, sentiment, and subjectivity in text (Pang et al., 2002).

Working with social network data, we address that opinion mining naturally has Big Data applications, considering the large quantity of information have to be processed in a faster way, enabling sentiment-related insights that would be hard to determine with small data amounts (Thelwall, 2016).

3. Methods

In this research, we perform a mixed method approach. First, the qualitative part of this study was conducted through contrasting the existing literature with practitioners' perspectives from interviews with IT and management consulting firms located in Spain, providing evidence about what do consulting firms mean by innovation.

Second, the quantitative part of the analysis of tweets posted in the Twitter Social Network of Spanish KIBS between March 2016 and March 2017. We carry out a machine learning approach on data in order to get analytical outputs.

3.1 Data

3.1.1 Qualitative Analysis: Collected from Interviews

Table 2 compiles the companies involved in the qualitative interviews. All the informants are responsible for the innovation management of the Spanish office. Interviews were conducted in Spanish between March 2016 and June 2016 using an interview protocol for a semi-structured interview containing five main areas: definition of innovation, innovation process, actors involved in the innovation process, an example of an innovative project, changes in the business model due to innovation.

Firm	Consulting Type	Size	Responsible	Interview Length	Brief profile
A	Information Technology and Services	Large	Innovation Director & Innovation Manager	60 min.	Global professional service firm that provides strategy, consulting, digital, technology and operational services in more than 120 countries.
B	Information Technology and Services	Medium	Innovation Director	63 min.	Innovation and technology service firm focused on digital transformation.
C	Management Consulting	Medium	Innovation Manager	45 min.	Local service firm focused on transportation, new technologies, and social knowledge.
D	Management Consulting	Large	Chief Innovation Officer	67 min.	Multinational professional service firm that provides audit, tax, consulting and advisory services in more than 150 countries.
G	Management Consulting	Medium	CEO & Innovation Manager	50 min.	Business corporation offering professional services in management and organizational consultancy, IT, human resources, support to the third sector, international financing and strategic innovation in Spain and Portugal.

L	Information Technology and Services	Large	Innovation Director	45 min.	Global innovation, engineering, and high technology consulting firm operating in more than 20 countries.
O	Information Technology and Services	Large	Innovation Manager	45 min.	Multinational consulting firm specialized in technology in Spain and Latin America.
T	Information Technology and Services	Large	Innovation Director & Industry Director	73 min. & 62 min.	Multinational consulting firm specialized in technology in Spain, Portugal, USA and Latin America.
V	Information Technology and Services	Large	Director of Innovation, Strategy and New Technologies	57 min.	Digital and technology service provider focused on digital and technological transformation in Europe and Latin America.

Table 2. Qualitative sample

3.1.2 Quantitative Analysis: Collected from Twitter

For this work, we have focused on their mentions on Twitter, regarding with the nine interviewed companies listed in Table 2. Data were gathered from a sample of 16.702 public tweets retrieved through Python language, helped with the Twitter Scraper library. For this study, we have considered only the text attribute, instead the other common metadata present on tweets, e.g. creation date, favorites, retweets, tweet identity number, user identification number and user name.

Large KIBS	Tweets	SME KIBS	Tweets
A	4371	B	1350
D	3690	C	27
L	1670	G	184
O	479	**Total SME**	**1561**
T	4512		
V	419		
Total Large	15141	Total Large + SME	**16702**

Table 3. Quantitative data sample

For our data collection, we have retrieved posts from their Twitter social networks between March 2016 and March 2017, as can be seen in Table 3.

3.1.3 Data Preparation

After the first step regarding data collection and preceded tweets and interviews cleanup, it is precise to extract term features applying text processing with techniques such as term frequencies, stop words removal and feature selection.

Then, established the corpora, defined as a collection of authentic machine-readable text (Xiao, 2010) coming from interviews and Twitter, we proceed the NLP stage.

In this juncture, we implemented R language as a tool for processing and developing models for this study. R is a language and framework for statistical computing and graphics. With the help of the R library "tm" (Feinerer et al., 2008) we have accomplished the text mining of our database and the following tasks, and we briefly explain the steps involved in the corpus transformation regards to the process of NLP techniques, according to previous works (Dubiau & Ale, 2013; Jurafsky & Martin, 2009).

- Text Normalization: The whole text, need to be normalized, in order to have internal coherence, dealing with idiosyncrasies of abbreviations, numbers, odd characters, non-standard words, among other pre-process.
- Tokenization: Also named word segmentation, consist of separating out words from running text, and indicates a word or sentence separated by a space in white or special characters.
- Filtering: Basically, consist cleaning raw data, removing url links, twitter particular words, e.g. "rt" which means "retweet", auto-mentions, emoticons, just to name few tasks.
- Stemming: In information retrieval, it is allowed to obtain the stem of a word, i.e. stripping off words endings. It is made with the help of the stemming algorithm called the Porter Stemmer.
- Lemmatization: It is another way to unify terms that provide the same information, replacing common words for the same lemma. For example, come, came and coming, are three forms of the verb to come. The word to come it is called the common lemma of these words, and mapping from all of these to come is called lemmatization.
- Other pre-processing's steps: Includes stopwords removal, i.e. articles such as "a", "an", "the", "to", etc. which are words that their information value is almost zero. Correct grammatical errors, removing punctuation, repeated characters, commas, numbers, to lowercase in text corpora.

3.2 Data Analysis: Unsupervised Learning

In this section, we present the outlines of our unsupervised learning analysis, regards of the data extracted from Twitter and interviews. Thus, we explain our approach as expressed in Figure 1.

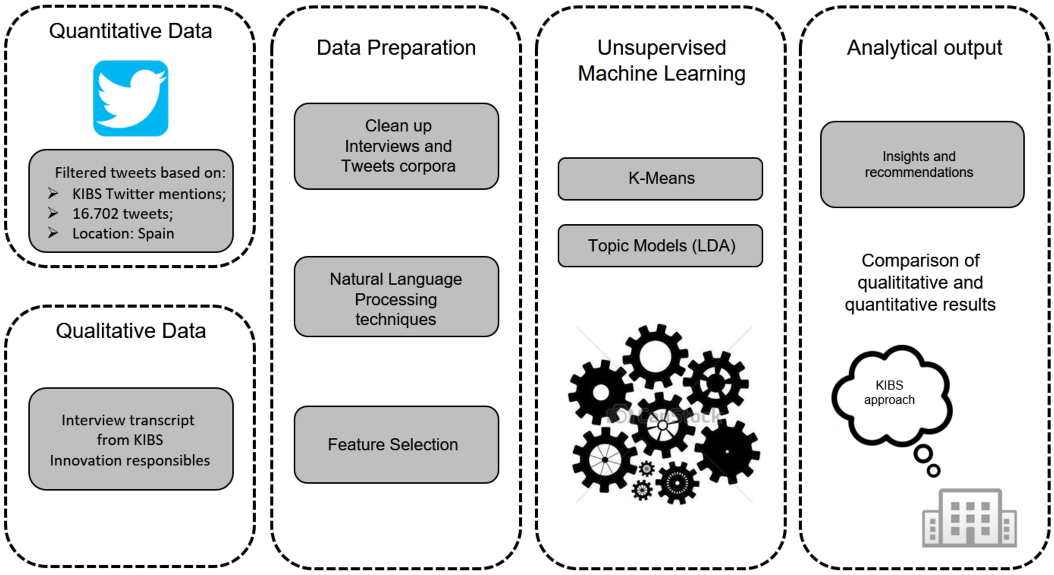

Figure 1. Framework of the approach proposed

3.2.1 *Text Classification*

Text Classification, also known as categorization (Rusell & Norvig, 2010), provides a text of some kind and it is decided which of defined class is belong to. For this purpose, we describe the main tasks implemented in our approach, to extract the features from data.

- Bag of words: The unigram (i.e. one-word) representation has been called the Bag of Words (BoW).
- Bigrams: He has considered the use of bigrams (i.e., two-word clusters) in order to capture more context, in general instead of a single word.

To this end, after looking at the results of the unigrams charts and the bigrams charts, we decided to present the results of the bigrams because the compound terms made more sense to understand the reason and correlation among innovation management concepts.

3.2.2 *K-means*

In this paper, we implemented the K-mean cluster analysis, that consists in a data reduction approach that is used to identify homogeneous cases groups, previously based on selected features (Jain, 2010). For this endeavor, we based our implementation of the K-means algorithm which was described in the work of Jain, 2010.
Between the clustering analysis techniques, we carried out the K-means classification, to discover competitive differentiation patterns in the information behind the data of interviews and tweets, our base corpora text.

3.2.3 *Latent Dirichlet Allocation (LDA)*

Topic models such as Latent Dirichlet Allocation (LDA: (Blei et al., 2003)) is a Bayesian estimation technique which assumes each document is a mixture of topics. Applying LDA, each group could be described as a distribution of a list of words inside the documents of our corpora. In fact, LDA is a generative model that allows documents to be explained by unobserved latent models (Khadjeh Nassirtoussi et al., 2014).

4. Results

The results have considered size as a control variable. Therefore, we have structured the results separating the perception of innovation for Large and SME consulting firms.

4.1.1 *PYRAMID PLOT-BIGRAMS*

Figure 2 shows a comparison of the main topics discussed in both the interviews and the tweets for Large Firms. Digital Transformation the most cited topic in both data sets, which is associated with other related popular terms such as big data and new technology. The tweets also bring some interesting insights about the focus of the innovation clients in large consulting firms: the financial sector is the most targeted one among other Spanish enterprises, the digital transformation discourse is enriched with the terms artificial intelligence and digital world. The importance of innovation structure to manage innovation is supported by the terms innovation center, project manager, job position and business unit.

It is important to note that interviews identify a topic that is not very common in tweets: new service, which reflects the priority given by the top management to create new offerings for their clients to be innovative and competitive.

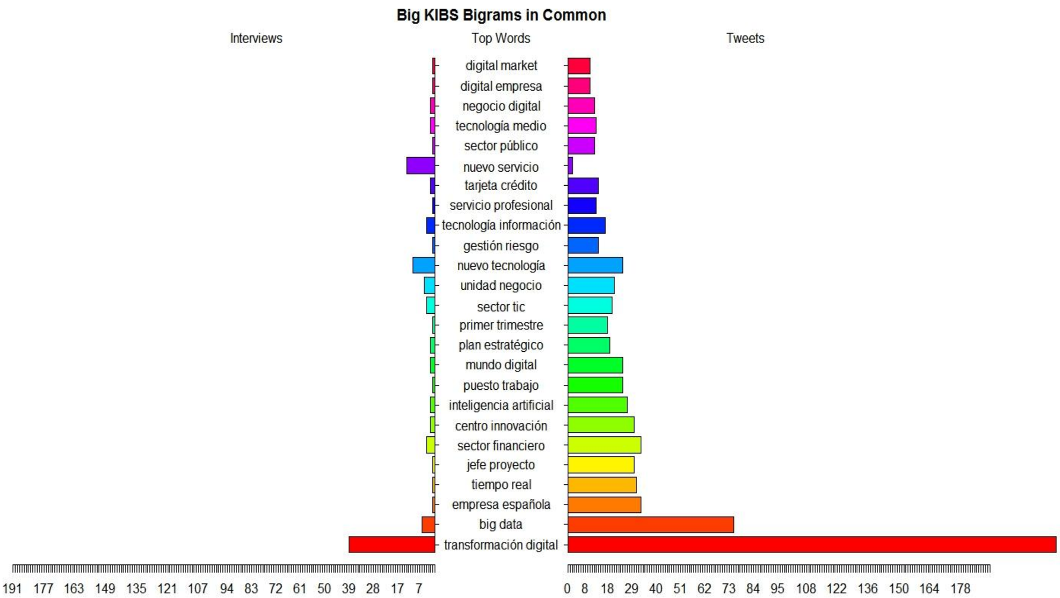

Figure 2. Common Topics Frequency in Large KIBS

Figure 3 shows a comparison of the main topics discussed in both the interviews and the tweets for SME Firms. We find that the terms business model and big data are highly cited in both data sets.

In one hand, when it comes to the interview, the discourse goes in terms related to the business model jargon such as value proposal and model design, as well as terms related to actors involved in the innovation process such as client company, any employee, and organizational innovation.

In the other hand, tweets support terms related to IT systems development such as teamwork, technology experience, use case, business design and user experience.

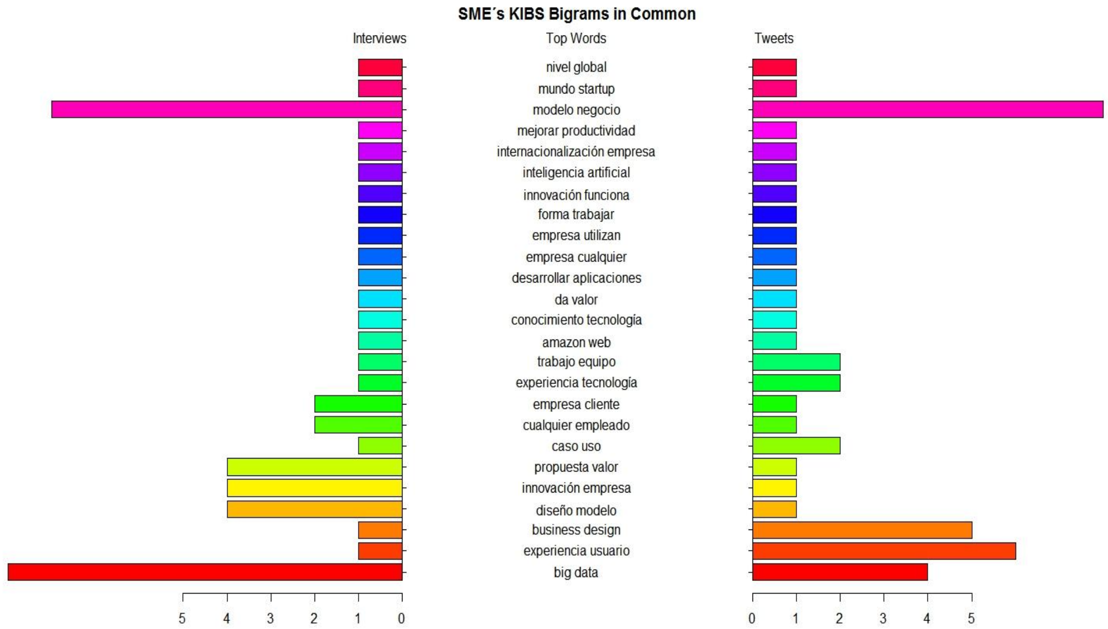

Figure 3. Common Topics Frequency in SME KIBS

4.1.2 *K-MEANS APPROACH*

Table 4 shows the concept clustering coming from the interviews and tweets. If we look only at the cluster in interviews, both SMEs and Large KIBS have a strong presence of two concepts: innovation and client and the name of Firm B, and to a lesser extent project, which represents that most of the innovative endeavors considers the client as the center that guides the new services offering unlike technology, environment, competitors, society, etc.

Tweets tell a different story about clusters; there are no clear dominant terms. However, most of the clusters for both SME and Large KIBS represent innovation events organized or attended by this firms, as well as specific news that went viral such as acquisitions or job offers.

Interviews		Tweets	
SMEs	**Large**	**SMEs**	**Large**
Cluster 1: enterprise project case idea client	Cluster 1: client product process service model	Cluster 1: job devops program madrid team	Cluster 1: madrid technology new center innovation
Cluster 2: product client idea B value	Cluster 2: innovation enterprise client project	Cluster 2: disrupt team event enterprise madrid	Cluster 2: programmer analyst job work madrid
Cluster 3: innovation person process radical enterprise	Cluster 3: innovation company idea process project	Cluster 3: devops tech cibank program talk	Cluster 3: consultancy opa enterprise spain
Cluster 4: B business product new project	Cluster 4: company service area client spain	Cluster 4: ux experience design chus chatbot	Cluster 4: market business new consultancy opa

Cluster 5: value person project area innovation	Cluster 5: client new service idea people	Cluster 5: bigdata enterprise technology awesome	Cluster 5: digital transformation new spain person
Cluster 6: technology new B enterprise lab	Cluster 6: innovation new area sector model	Cluster 6: codemotion stand congressritsi tchfest bank	Cluster 6: job work offer coruña analyst
Cluster 7: innovation B lab area concept	Cluster 7: digital technology transformation cliente process	Cluster 7: new project know team tech	Cluster 7: sector trend consultancy opa spain
Cluster 8: firm B innovation area lab person	Cluster 8: innovation process company business model	Cluster 8: technology awesome disrupt devops madrid	Cluster 8: madrid job spain work programmer

Table 4. KIBS Interviews and Tweets Clustering K-means

4.1.3 LDA APPROACH

LDA technique was used as a means of cluster triangulation, so to have a different perspective about possible word clusters in both interviews and tweets. Table 5 shows the concept results organized by Topic (cluster), which are very similar to the ones in Table 4 corroborating the main topics in the qualitative and quantitative data.

	Topic 1	**Topic 2**	**Topic 3**	**Topic 4**	**Topic 5**	**Topic 6**	**Topic 7**	**Topic 8**
SME - Interviews	innovation, product, enterprise, B, project, business	value, project, person, view, innovation, knowledge	innovation, enterprise, new, technology, transformational, area	innovation, process, idea, say, final, profile	client, methodology, innovation, project, startup,	product, view, room, B, idea, client	technology, opportunity, case, business, new, startup	innovation, B, person, area, lab, data
Large - Interviews	digital, enterprise, transformation, innovation, business, service	innovation, process, culture, company, objective, T	innovation, new, company, area, client, service	office, client, service, process, transference, person	innovation, project, idea, some, theme, clear	innovation, client, service, theme, different, new	company, innovation, service, model, market, new	company, technology, client, process, innovation, new
SME - Tweets	new, team, techandbeers, learning, campusmadrid, tool	job, awesome, devops, chus, nievesas, program	event, disrupt, cloud, hapiness, bank, beeday	Bank, talk, uxspain, partner, mvp, work, know	ux, api, design, tchfest, meetup, vr	disrupt, congresoritsi, issecurity, bcardboard, business, ceetsectorial	blockchain, employee, hackaton, devops, good, blockchainday	technology, codemotion, tech, dato, video, bigdata
Large-Interviews	madrid, job, spain, consultancy, opa, programmer	consultancy, digital, new, enterpise, trend, spain	digital, new, madrid, opa, trend, work	enterprise, innovation, opa, spain, technology, digital	digital, work, job, opa, technology, professional	digital, spain, innovation, work, new, opa	opa, enterprise, coruña, prize, barcelona	consultancy, new, madrid, opa, spain, launch

Table 5. KIBS Interviews and tweets topic modeling

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5. DISCUSSION

The innovation focus by KIBS size group is summarized in Table 6. These summarized results are the base for the discussion.

Results	Large Firms	SME Firms
Common topics	Digital technologies (i.e. Big Data)	
Distinctive topics	Innovation with clients Innovation structure New Services	Business Model Innovation Actors IT System Development

Table 6. Innovation Focus by KIBS Size Group

The first interesting part is the prevalence of digitalization as a key driver for innovation despite other current trend drivers such as globalization or sustainability. Gastaldi et al. (2015) state that the fourth generation of continuous innovation, named "Open Collaborative Ecosystem" is enabled by the use IT Resources, IT Capabilities, IT Investments and Decision Support Systems, which can explain why KIBS, especially Consulting Firms, have digitalization as their strategic priority.

This priority is the one that makes formalized the innovation process by creating structures that allow them to channel and exchange knowledge among the different innovation actors inside and outside the KIBS firm (Bessant & Rush, 1995; Tiidd & Bessant, 2014). There is still little research about the innovation structures that allow the creation of this open, collaborative ecosystems as well as when this practice is not good for innovation (Bogers et al., 2016; West et al., 2014). Besides, with the rise of services as the most important part of a country's economy claims for new business models that provide new or updated service offerings (Nair et al., 2013; Tether & Tajar, 2008).

Regarding our analysis approach, K-means and LDA; performed the partition of disjoint K clusters after a number of iterations grouped by centroids, for one side, and the assignment of our document (in our case the corpus of interviews and tweets) a mixture of topics categorized, respectively, we found out no significant differences in the interpretation models: recurrent terminologies are present in both sides, e.g. innovation, technologies, and occurrences of certain companies related with KIBS in both methods, showing us the strong similarity, in the perception in this study case.

6. CONCLUSION

This paper contributes to the understanding of innovation management in the context of KIBS. It also sheds light on the use of mixed methods using qualitative interviews and big data techniques to analyze tweets in the Spanish language. Indeed, it adds knowledge to the use new mixed qualitative and qualitative methods in innovation management studies. As a final point, it contributes to the use of machine learning. There is a limitation for reliability in the use of tweets for big data analysis because people tend to post more positive comments and neglect the publication of complaints and negativity.

It would be interesting to conduct more mixed methods studies having a multinational Twitter database as well as other types of KIBS. It would be interesting to further develop an organization model to generate knowledge for decision making based on social media analysis. i.e. to estimate the relationship between a service provided by KIBS and innovation or marketing campaign used to disseminate information.

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